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Heat Waves and Health Outcomes in Alabama (USA): The Importance of Heat Wave Definition

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Abstract

Background: A deeper understanding of how heat wave definition impacts the relationship between heat exposure and health, especially as a function of rurality, will be useful for development of effective heat wave warning systems.

Objective: Compare relationships between different heat wave index (HI) definitions and preterm birth (PTB) and non-accidental mortality (NAD) across urban and rural areas.

Methods: A time-stratified case-crossover design was used to estimate associations of PTB and NAD with heat wave days (defined using 15 HIs) relative to non-heat wave control days in Alabama, USA (1990-2010). ZIP code-level HIs were derived using data from the North American Land Data Assimilation System. Associations with heat wave days defined using different HIs were compared by bootstrapping. Interactions with rurality were examined.

Results: Associations varied depending on the HI used to define heat wave days. Heat waves defined as at least two consecutive days with mean daily temperatures above the 98^{th} percentile were associated with 32.4% (95% CI: 3.7, 69.1%) higher PTB, and heat waves defined as at least two consecutive days with mean daily temperatures above the 90^{th} percentile were associated with 3.7% (95% CI: 1.1, 6.3%) higher NAD. Results suggest significant positive associations were more common when relative, compared to absolute, HIs are used to define exposure. Both positive and negative associations were found in each rurality stratum. However, all stratum-specific significant associations were positive, and NAD associations with heat waves were consistently positive in urban strata, but not middle or rural strata.

Conclusions: Based on our finding, we conclude that a relative, mean temperature only heat wave definition may be the most effective metric for heat wave warning systems in Alabama.

Introduction

Climate change is expected to result in more frequent, intense, and longer heat waves (Meehl and Tebaldi 2004). Increased mortality associated with heat waves is well documented (Basu 2009), and recent research suggests heat waves may increase adverse birth outcomes (Basu et al. 2010; Strand et al. 2011a). However, most US-based research examining associations between heat and health outcomes have focused on urban areas in Northeastern and Midwestern regions. Furthermore, there has been little published on whether national heat wave warning systems are appropriate for all regions. The Southeastern United States, particularly in the Deep South states of Alabama (AL), Mississippi, Louisiana, South Carolina, and Georgia, compared to the rest of the US, have different climate patterns characterized by long, hot summers with higher minimum temperatures and humidity. There are also profound differences in demographic compositions, housing quality and characteristics, and urban-rural land-use and vegetation patterns (Bonan 1997; Brown et al. 2005; Golant and LaGreca 1994).

Previous studies examining associations between heat waves and health outcomes have used a variety of heat wave metrics, making it difficult to compare results or determine the most appropriate metric for public health warning systems. Heat wave indices (HIs) are defined using temperatures only or temperatures and other meteorological factors such as humidity and wind speed, and have either absolute or relative temperature thresholds that must be exceeded for a specified duration ranging from one to multiple consecutive days (Smith et al. 2013). An examination of 16 previously published HIs for the period 1979-2011 in the US shows substantial differences in heat wave geographic patterns and time trends by HI definition (Smith et al. 2013). Previous studies have reported stronger positive associations between heat waves and mortality in Northeastern and Midwestern cities compared with Southeastern cities

(Anderson and Bell 2011; Basu 2009), which suggests that acclimatization may contribute to region-specific exposure-response relationships, and that heat wave metrics and warnings may need to be regionally specified (Barnett et al. 2010; Bobb et al. 2011; Vaneckova et al. 2011).

Several recent studies highlight the need to increase our understanding of extreme heat events and adaptation strategies in rural versus urban areas (Huang et al. 2011; Knowlton et al. 2007; Reid et al. 2009). Previous studies have reported evidence suggesting that excess mortality and morbidity due to extreme heat events in urban environments are related to the presence of vulnerable populations and the urban heat island effect (Basu 2009; Huang et al. 2011; Kovats and Hajat 2008). Rural communities, though not as well studied as urban communities, may have unique vulnerabilities, such as increased distance to care, greater time spent outdoors, and lack of heat wave response systems (e.g., cooling centers) (Merwin et al. 2006; Weisskopf et al. 2002). Land-use patterns and demographic compositions in Deep South urban and rural regions differ from regions analyzed in previous heat wave health studies. In particular, Deep South states have more poorly maintained housing stock, higher poverty, and both urban and rural areas with large non-Hispanic African American populations (Golant and LaGreca 1994).

We analyzed Alabama birth and death records to examine whether (1) using different HIs results in differing associations between heat waves and health outcomes and (2) associations between heat waves and health outcomes differ by rurality.

Methods

Vital Records and Outcomes

Live birth and death records were received from Alabama Department of Public Health (ADPH) for May to September, 1990 to 2010. The study protocol was reviewed and approved through ADPH Institutional Review Board and University of Alabama at Birmingham Institutional Review Board (Protocol #X110706005).

Live birth records included the date of birth, gestational age, birth weight, and the mother's residential ZIP code. After excluding 81 births with unlikely weights (< 200 grams) (Wolf and Armstrong 2012), 62,803 (out of 543,980 births) were classified as preterm births (PTBs), having gestational ages between 24 and 37 weeks (Morgan et al. 2008). Of these, 60,466 PTBs had birthdates, residences in Alabama ZIP codes, and available meteorological and rurality data.

Death records indicated the date of death, the deceased's residential ZIP code, and International Classification of Diseases (ICD) 9th or 10th revision cause of death code. Of 381,776 deaths in Alabama (1990-2010), 347,432 deaths were non-accidental (ICD-9 codes < 800 and ICD-10 codes with letters A through R) (Crouse et al. 2012). Of these, 301,126 non-accidental deaths (NADs) had associated dates, residences in Alabama ZIP codes, and available meteorological and rurality data.

Heat wave indices

Sixteen HIs were identified from the public health and climate change literature (Anderson and Bell 2009; Anderson and Bell 2011; Hattis et al. 2012; Meehl and Tebaldi 2004; Peng et al. 2011; Robinson 2001; Rothfusz 1990; Steadman 1979; Steadman 1984; Tan et al. 2007), as well as from indices used by the National Weather Service to develop a public warning system (Rothfusz 1990; Steadman 1979). Complete definitions, calculation methods, and heat wave geographical patterns by 6 continental US regions and temporal trends during 1979 to 2011 of these 16 HIs have been described previously (Smith et al. 2013) and short definitions are shown in Table 1. Briefly, meteorological data (temperature, specific humidity, surface pressure, surface downward shortwave radiation, surface downward longwave radiation, and directional wind components) on a 12.5 km grid from the Phase 2 of the North American Land Data Assimilation System (NLDAS-2) (Cosgrove et al. 2003) for the period 1990 to 2010 were used to develop daily ZIP code-level HI estimates for the current study (Smith et al. 2013). Heat wave days were identified at the ZIP code-level using each day's meteorological variables. Relative HIs were based on the individual ZIP code's 1990 to 2010 meteorological history. If more than 50% of land area within a ZIP code was above the specific HI threshold on a given day, the ZIP code was determined to be in a heat wave. ZIP codes, obtained from either the mother's residence (birth records) or deceased's residence (death records), were used in combination with the event day (i.e., the day of preterm birth or the day of death) to merge vital records with the Census ZIP Code Tabulation Area-based HIs. HI16 was eliminated from further analysis, since no heat wave days occurred in Alabama during the study period according to this definition. There were 640 ZIP codes used with a mean area of 226 km^2 (standard deviation = 200).

Rurality measures

Vital records were merged with two ZIP code-level measures of rurality. First, Rural-Urban Commuting Area Codes (RUCA) version 2.0 (Hart et al. 2005) were classified using the suggested "categorization B", which divides between "urban focused", "large rural city/town (micropolitan) focused", and "small rural and isolated town focused" categories. The rural

RUCA category, consisting of areas with low commuting patterns to census places ≥10,000, represents populations most economically disconnected from cities and larger towns (Hart et al. 2005; Kent et al. 2013). Second, Census 2000 population densities were classified into tertiles with the highest tertile capturing the most population-dense urban areas. In addition to these measures of rurality, summertime maximum 16-day green vegetation fraction (GVF), a measure of percent live vegetation cover, was derived from Moderate Imaging Resolution Spectrometer (MODIS) satellite sensor data at 1km resolution (Zeng et al. 2000). To calculate a ZIP code-level GVF value, we took an average of 1km GVF grid cells that had centroids within a ZIP code. GVF was calculated for 2004, a typical, non-drought year in Alabama. GVF was divided into tertiles for analyses.

Study design and analysis

We used a time-stratified case-crossover design (Basu et al. 2005; Crouse et al. 2012; Janes et al. 2005b). A case-crossover design emulates a retrospective nonrandomized crossover study; in this design each case event (either PTB or NAD) is matched with a counterfactual control exposure period (Maclure 1991). In the time-stratified sampling design, all days that are on the same day of the week and within the same month as the case day are selected as control periods. The time-stratified control selection method is frequently used in environmental health studies because it controls for time trends, seasonality, and overlap bias (Basu et al. 2005; Crouse et al. 2012; Janes et al. 2005a, 2005b; Tong et al. 2012). Case-crossover data are analyzed in the same manner as a matched case-control design, using the case and matched time-stratified control periods as stratum in conditional logistic regression models (Wang et al. 2011). Analyses were run using SAS 9.3 (Cary, NC) and splines in conditional logistic regression models were performed using the LGTPHCURV9 macro (Li et al. 2011).

Lags, duration, and seasonality

To determine if associations of PTB and NAD with heat waves varied according to characteristics of the heat wave, we examined associations of each outcome with heat wave days (defined using the 15 HIs) versus non-heat wave control days on the same day as the event (i.e., the day of birth or death, lag0) and up to 6 days before the event (lag1 to lag6). Previous studies have reported associations between acute morbidity and heat within a few days of the outcome, with days further back in time carrying null associations (Ye et al. 2012). To compare our results with previous studies, we examined whether lag0 associations changed when we adjusted for daily mean temperature as a natural cubic spline with three degrees of freedom and equally spaced knots (Anderson and Bell 2009). We performed separate analyses to determine whether the timing of the heat wave influenced associations. Specifically, we ran models that included a product term between heat wave days and a variable indicating whether the heat wave day occurred during the first heat wave of the season, and also ran a second set of models that included product terms between heat wave days and a variable indicating whether the heat wave occurred early in the season (May to July) or late in the season (August to September). To examine modification of associations according to the duration of heat waves, we determined the median length of heat waves (in each of our birth record and death record samples) defined according to each HI, and estimated associations separately for heat wave days during heat waves that were shorter than the median duration and heat wave days during heat waves that were greater than the median duration. We used conditional logistic regression models to estimate odds ratios (ORs) and 95% confidence intervals (CIs) for the associations between heat wave days and PTB or NAD, and reported associations as the percent difference in the odds of the outcome on heat wave days compared with non-heat wave days [percent difference = (OR –

1) × 100]. We used Akaike's Information Criterion (AIC) values to estimate relative goodness of fit across the models (Bozdogan 1987).

Estimating model parameter differences

Based on AIC values and previous applications of the HIs, we selected six HIs to examine further. To estimate whether there were significant differences in parameter estimates across the models, we calculated bootstrapped bias-corrected percentile-based CIs. We calculated the CIs using 999 samples with replacement and determined the bias-corrected 2.5 and 97.5 percentiles (Ajmani 2009; Carpenter and Bithell 2000; UCLA: Statistical Consulting Group 2012). If a bootstrapped 95% CI for the difference between two point estimates on the lnOR scale did not include zero, we considered the two estimates to be significantly different ($p < 0.05$).

Estimating effect modification by rurality

We modeled multiplicative interaction terms between RUCA categories and heat wave days to determine if associations differed among ZIP codes classified as urban, large town, or small town. In addition, we estimated associations according to tertiles of population density and GVF as alternative measures of rurality.

Results

Distribution of heat waves and cases on heat wave days across HIs

Table 1 shows the numbers of PTBs and NADs that occurred during heat waves varied depending on the HI definition used. For example, when heat waves were defined using HI04 (mean daily temperature > 99th percentile for ≥ 2 consecutive days) each ZIP code had an average of 0.01 heat wave days/season, resulting in a total of 1 PTB and 11 NADs on heat wave days during 1990 to 2010. In contrast, when heat waves were defined using HI13 (maximum daily heat index > 80°F for ≥ 1 day), each ZIP code had an average of ~ 125 heat wave days/season (82% of the 153 days from May to September), and over 80% of all PTB and NAD occurred on days classified as a heat wave day.

Associations with heat waves defined using different HIs

Associations between heat wave days and PTB were positive for heat waves defined by 9 of the 15 HIs when models were not adjusted for mean daily temperature (Figure 1A and Supplemental Material, Table S1). Positive associations with heat waves defined using HI01 (mean daily temperature > 95th percentile for ≥ 2 consecutive days) and HI03 (mean daily temperature > 98th percentile for ≥ 2 consecutive days) were statistically significant, with 11.6 % (95% CI: 0.9, 23.4%) and 32.4% (95%CI: 3.7, 69.1%) higher odds of PTB on heat wave versus non-heat wave days, respectively. Associations with heat wave days defined using HIs based on mean daily temperatures increased as the threshold temperature increased from the 90th percentile (HI02, 1.5% higher PTB; 95% CI: -3.5, 6.9%) to the 95th and 98th percentiles (HI01 and HI03, respectively), but PTB was negatively associated with heat wave days when the mean daily temperature threshold was > 99th percentile (HI04, 33.3% lower PTB; 95% CI: -92.4, 453.9). However, as already noted, there was only one PTB during the study period based on the more stringent HI04 definition. When heat waves were defined using HI12, which requires exceeding both minimum and maximum daily temperature thresholds for ≥ 2 consecutive days, the odds of PTB was significantly lower on heat wave days compared with non-heat wave days (9.7% decrease; 95% CI: -16.4, -2.5%). Although a total of 1,203 PTB occurred on heat wave days defined using HI12, HI12 heat waves were almost entirely limited to ZIP codes in the southwest corner of Alabama, on the Gulf of Mexico (Figure 2C).

Associations between heat wave days and NAD were positive for heat waves defined by 7 of the 15 HIs (without adjustment for mean temperature) (Figure 1B and Supplemental Material, Table S1), and associations were statistically significant for heat waves defined by 3 of the HIs. Specifically, the odds of NAD were higher in association with heat wave days defined by HI02 (mean daily temperature > 90^{th} percentile for ≥ 2 consecutive days, 3.7% higher; 95% CI: 1.1, 6.3%), HI07 (based on 2 maximum daily temperature percentile cutoffs for at least consecutive 3 days, 5.5 % higher; 95% CI: 1.0, 10.2%), and HI09 (maximum daily apparent temperature > 90^{th} percentile for ≥ 1 day, 2.0% higher; 95% CI: 0.3, 3.8%). Associations between NAD with heat wave days defined using HIs based on maximum daily apparent temperatures increased as the threshold apparent temperature increased from the 85^{th} percentile (HI08, 1.2% higher NAD; 95% CI: -0.1, 2.5%) to the 90^{th} (HI09, 2.0% higher NAD; 95% CI: 0.3, 3.8%) and 95^{th} percentiles (HI10, 2.7% higher NAD; 95% CI: -0.2, 5.7%). There was no evidence of a positive exposure-response for PTB and apparent temperature HIs.

When models were adjusted for mean daily temperature, there were no statistically significant positive associations between heat wave days and PTB or NAD (for any HI), and adjustment moved some positive associations closer to the null (HI01 and HI03 heat wave days with PTB and HI02, HI07, and HI09 heat wave days with NAD) (Supplemental Material, Table S1). Others changed from positive to negative, and the negative association with heat wave days defined using HI09 became statistically significant (4.7% lower odds of PTB, 95% CI: -8.5, -0.6%). However, adjusting for mean daily temperature had little effect on associations between heat wave days and PTB or NAD when heat waves were defined based on absolute values [versus relative (percentile) thresholds] for heat index (HI13, HI14, HI15), maximum daily temperature (HI11), or minimum and maximum daily temperature (HI12).

Differences in associations according to heat wave qualities

We next evaluated modification of associations according to lags, heat wave duration, and seasonality (without adjustment for mean temperature). Out of 10 relative HI lag0 models, 2 had significant relationships with PTB and 3 had significant relationships with NAD (Figure 1 and Supplemental Material Table S1). All significant relative HI associations were positive. Out of 5 absolute HI lag0 models, one had a significant negative relationship with PTB and none had significant relationships with NAD. Associations did not change from positive to negative with longer lags, as would be expected with mortality displacement (Figure 3 and Supplemental Material, Figure S1). Longer duration heat waves numerically increased point estimates of associations (i.e. closer to the null for negative associations and further from the null for positive associations) with health outcomes for 10 of 15 HIs examined in PTB duration models and 7 of 15 HIs examined in NAD duration models (Supplemental Material, Figure S2). Associations between heat wave days and the outcomes were generally consistent between the first heat wave of the season and subsequent heat waves or between early and late season heat waves (data not shown).

Evaluation of model fits and differences in parameter estimation across HIs

AIC is a relative measure of information lost when fitting the model, hence smaller AIC values suggest better fitting models. AIC values differ by more than 2 for models containing different HIs (Supplemental Material, Table S2), indicating there are likely differences in model fits (Burnham and Anderson 2004). Models of heat waves defined using HI02 had the lowest AIC across the NAD models, whereas models of heat waves defined using HI12 carried the lowest AIC among all PTB models. Across PTB models, models of heat waves defined using HI01 and HI03 had similar fits (AIC differences =2.35 and 1.92, respectively) to models including HI12.

HI12 had a negative association with PTB, whereas HI01 and HI03 had positive associations with PTB. Across NAD models, models of heat waves defined using HI07 and HI09 had similar fits (AIC differences =2.03 and 2.55, respectively) to models including HI02. HI02, HI07, and HI09 all had positive associations with NAD.

HIs 02, 03,07, 09, 12, and 15, which offer a representation of the different types of HIs used to define heat waves in previous epidemiological analyses and for heat wave warning systems, were examined in further detail. Bias-corrected percentile-based bootstrapped confidence intervals indicate that in PTB models using HI03, associations are significantly numerically higher than HI09, HI12, and HI15 associations, while HI12 associations are significantly numerically lower than HI02 and HI07 estimates. For NAD models, HI07 associations were significantly numerically higher than HI12 and HI15 associations.

Differences in associations according to rurality categories.

Since the mean daily temperature HIs (HI01to HI03) had simple definitions at different relative temperature cut-points for defining a heat wave, and significant associations with adverse outcomes (HI01 and HI03 for PTB, HI02 for NAD), we chose these heat wave metrics to examine whether associations differed by rurality.

All statistically significant rurality-specific associations between heat wave days and PTB were positive (Figure 4A to 4C). Heat wave days defined by HI03 were positively associated with PTB in ZIP code areas with populations in the lowest (59.9% increase; 95% CI: -0.5, 155.6%) and middle (75.0% increase; 95% CI: 20.7, 153.8%) tertiles of population density, but were negatively associated with PTB in ZIP code areas with populations in the highest tertile of population density (23.1% decrease; 95% CI: -51.6, 22.2%) (p-value for HI03 and population density = 0.02) (Figure 4B). Heat wave days defined by HI02 were positively associated with PTB in ZIP code areas with the highest vegetation (9.6% increase; 95% CI: 0.1, 20.1%), but there was little evidence of associations for ZIP codes with medium (4.9% decrease; 95% CI: -13.0, 4.0%) or low vegetation (0.5% increase; 95% CI: -8.3, 10.1%) (p-value for HI02 and GVF = 0.09) (Figure 4C). All other HI*rurality interaction terms in PTB models had p-values > 0.10.

All statistically significant rurality-specific associations between heat wave days and NAD were positive (Figure 4D to 4F). Associations between heat waves and NAD were consistently positive in the urban category for every HI*rurality model, except for the association between HI03 heat wave days and NAD in the RUCA urban category (2.7% decrease; 95% CI: -15.2, 11.6%), but the interaction term in this model was not significant (p-value for HI03 and RUCA interaction p-value = 0.32) (Figure 4D). Urban categories were consistently numerically higher in heat wave by rurality models with interaction p-values ≤0.10. HI01 heat wave days showed a positive association with NAD in the RUCA urban regions (4.8% increase; 95% CI: -10.9, 10.9%), a closer to the null association in RUCA large town regions (1.8% increase; 95% CI: -10.7, 16.0%) and a negative association in RUCA small town regions (10.9% decrease; 95% CI: -21.1, 0.7%) (p-value for HI01 and RUCA = 0.07) (Figure 4D). HI01 heat wave days showed a positive association with NAD in the most population dense tertile (7.2% increase; 95% CI: -1.5, 16.7%) and middle density tertile (2.9% increase; 95% CI: -5.5, 11.9%), but a negative association in the least population dense tertile (76.1% decrease; 95% CI: -14.2, 2.8%) (p-value for HI01 and population density p-value = 0.10) (Figure 4E). All other heat wave by rurality interaction terms in NAD models had p-values > 0.10.

Discussion

In this analysis, we examined which HIs were most predictive of two important adverse health outcomes, PTB and NAD, using novel exposure and health outcome datasets covering both urban and rural areas in Alabama, USA. We found that compared with non-heat wave control days, heat wave days defined using HI02 were associated with 3.7% (95% CI: 1.1, 6.3%) higher non-accidental mortality, and heat wave days defined using HI03 were associated with 32.4% (95% CI: 3.7, 69.1) higher PTB. These positive associations were attenuated when adjusted for temperature, suggesting increases in temperature can account for some of the effects seen during heat waves.

Comparison of PTB results to previous findings.

Relationships between birth outcomes and heat waves have not been studied extensively. Another recent study in California that also used a case-crossover design reported that a 10°F increase in weekly temperatures was associated with an 8.6% increase in PTB (Basu et al. 2010). Other studies found a null association between temperature and gestation length and indicated that previous associations might be attributed to uncorrected bias in cohort study analyses (Strand et al. 2011a, 2011b; Wolf and Armstrong 2012). Our study suggests there may be a positive association between PTB and heat wave days defined using a percentile-based mean daily temperature metric. Associations between PTB and heat wave days defined using other metrics were not significant, with the exception of a significant negative association with heat wave days based on a previously used metric which in Alabama only exhibited heat waves in a small region of the state located on the Gulf of Mexico (Figure 2C). Region might play a role in differences in associations, as Basu et al. (2010) found that across 16 counties in California there were differences in associations between heat waves and PTB.

Comparison of NAD results to previous findings

Using data from 43 cities, Anderson and Bell (2011) found an average 3.7% increase in mortality associated with a heat wave defined as ≥ 2 consecutive days with mean temperatures > 95th percentile during May through September, but when separated by region reported a lower, non-significant association in the Southeast (1.8% increase; 95% CI: -0.11, 3.84%). Our unadjusted results showed a similar association. However, after adjusting for daily mean temperature the point estimate fell below zero (-2.2%; 95% CI: -7.4, 3.3%). Peng et al. (2011) examined the association between heat wave days defined using HI07 and mortality in Chicago, and reported a temperature-adjusted 7.8% (95% CI: 6.1, 9.5%) higher mortality, compared with a 3.3% (95% CI: -1.3, 8.2%) increase in our study. In the current study, unadjusted associations between relative apparent temperature defined heat waves (HI08 to HI10, with maximum daily apparent temperature thresholds of > 85th, > 90th, and > 95th percentile, respectively) followed similar patterns as in the Massachusetts-based Hattis et al. (2012), with more extreme heat waves having larger associations (Figure 1), although the associations found in the present study were smaller [(1.2 to 2.7% in current study, 3.7 to 5.3%, unadjusted in Hattis et al. (2012)].

Examination of overall heat wave effects among HIs

Our results suggest significant positive associations were more commonly present when relative, compared to absolute HIs were used to define exposure. This suggests public health warning systems may be more effective using regionally specific definitions. This finding is consistent with other studies (Knowlton et al. 2007) and suggests reliance on the absolute measures of the NWS alert system (HI13 to16) may not be optimal for protecting public health.

Previous physiological research shows that high temperatures, as well as increased humidity, heighten the risk of heat illness (Coris et al., 2004; Perry et al., 2011). However, our findings suggest that HIs including humidity and other meteorological factors [i.e., heat waves defined based on apparent temperature (HI08 to HI10) or heat index values (HI13 to HI16)] may not be more predictive of adverse heat-related health effects, which is consistent with previous research (Vaneckova et al., 2011). In addition, minimum or nighttime temperature has been shown to be predictive of mortality (Anderson and Bell 2011; D'Ippoliti et al. 2010), possibly due to decreased recovery time or association with humidity. We evaluated one metric based on minimum temperature alone (HI05, minimum daily temperature > 95^{th} percentile for ≥ 2 consecutive days), which had a non-significant positive association with PTB. Mean temperatures, which reflect both minimum and maximum temperatures, seem to be more predictive of health outcomes in the current study, which is consistent with previous studies (Anderson and Bell 2009; Barnett et al. 2010; Vaneckova et al. 2011).

Model power is variable due to the different number of classified heat wave days between HIs, due not only to the observed effect-measure strength, but also to the total number and geographical distribution of heat wave days. However, patterns in the mortality model results could still be seen comparing point estimates of associations between heat waves and health outcomes using HIs with similar proportions of cases on heat wave days across the 20 year period of study (HI02, HI06, HI10, HI11, and HI15; Table 1). From NAD models containing these five HIs, those with relative-scale cut-point definitions (HI02, HI06, and HI10) showed similar positive associations and had lower confidence limits that were above or close to zero

(Figure 1B). Models with absolute-scale cut-point definitions (HI11 and HI15) resulted in negative associations closer to zero. In PTB models using these five heat wave definitions, relative-scale cut-point HI-defined heat wave days had positive (HI02 and HI06) or near-null (HI10) associations, and absolute-scale cut-point HI-defined heat wave days had negative associations (Figure 1A).

Previous and current research highlights the importance of the choice of HI for interpretation of health effects related to climate change. Based on the current and previous analyses (Anderson and Bell 2009; Vaneckova et al. 2011), HIs based on mean daily temperature (such as HI01to HI03), may be the most useful and simplest metric for the US, although more comparative analyses at the regional level are needed. Smith et al. (2012) suggests the Southeast, compared to rest of the US, has experienced the most widespread increase in heat wave days from 1979 to 2011 across the majority of HIs (Smith et al. 2013). Specifically, increases in HI01, HI02, HI06, HI07, HI08, HI09, HI11, HI14, and HI15 have been larger in the Southeast, compared to most other US regions. HI02, HI06, HI09, HI11, and HI14 showed more than a half-day average increase in yearly number of heat wave days within the Southeastern US over the 1979 to 2011 period. From the perspective of projecting future climate change impacts, choosing HIs based on relative daily temperatures from these five metric metrics (i.e., HI02 and HI06) have a practical advantage, as they show positive associations with adverse health outcomes, and because projecting daily air temperature is a simpler (though not trivial) problem relative to projecting multiple meteorological variables at subdaily timescales, as is required by the more complex HIs.

Comparison of heat wave qualities across HIs

Previous studies suggest that associations between heat wave days and mortality are stronger during longer duration heat waves and during the first heat wave of the season (Anderson and Bell 2011). The present study suggests longer duration heat waves are associated with increases in the magnitude of the positive associations with NAD, although seasonality patterns were not found (Figure 3 and Supplemental Material, Figure S2, data not shown for seasonality).

Effect-measure modification by rurality across HIs

From current literature focused on urban areas, it is implied that urban regions have higher mortality risks from heat waves, although rural areas are rarely studied. Based on numerous studies, prominent risk factors for heat wave associated mortality include social isolation, poverty, and age > 65 (Ebi et al. 2006; English et al. 2009; Haines et al. 2006), which are prevalent in many rural areas. Yet these previous studies have used exposure variables (e.g., land surface temperature) in urban-suburban areas, not rural areas (Hondula et al. 2012; Johnson et al. 2009). Heat wave warning systems that use relative thresholds are typically based on average temperatures experienced in relatively large regions containing both urban and rural areas (Lowe et al. 2011). Results of the current study do not suggest strong effect modification by rurality for heat wave related PTB or NAD. Although NAD risk may be heightened in urban areas, with positive associations consistent in urban areas but not in more rural areas, most interaction terms between heat waves and rurality were not significant ($p > 0.05$). All significant rurality-specific associations were positive.

Potential limitations

As with previous studies examining relationships between heat waves and health outcomes, we did not have a measure of time spent outdoors to determine the degree subjects were exposed to ambient temperatures. Although air conditioning has been found to modify the association between temperature and mortality (Anderson and Bell 2009), as with most heat wave studies we did not have a measure of air conditioning. Also, this study did not adjust for air pollution. However, previous studies have found relationships between temperature and mortality to remain after adjustment for air pollution exposure (Anderson and Bell 2009). This study also only includes data from Alabama, so is not generalizable to other regions with different climates, demographics, and housing characteristics. As in most previous heat wave studies we did not adjust for the multiple comparisons that were examined.

Conclusions

Our results suggest that previous findings of associations between heat waves and adverse health outcomes may also apply in the Southeastern US state of Alabama. However, associations were highly variable depending on the measure used to define heat waves. Results demonstrate that the choice of HI can result in different association estimates when studying health effects of extreme heat events. These results have implications for operational warning systems and for studies designed to quantify health impacts of climate change. Interestingly it was not clear that including multiple health-relevant meteorological parameters in an index improved model fits or were more likely to find significant associations, suggesting that simple, temperature-only indices might be most appropriate for warning systems and climate impacts analysis. Finally, heat wave days were associated with PTB and NAD in both rural and urban areas, depending on the heat wave definition used, highlighting the need to develop heat wave response systems in both cities and rural areas.

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Table 1. Summary of heat wave indices (HIs), preterm birth (PTB, n cases = 60,466) and non-accidental death (NAD, n cases = 301,126) data in 640 Alabama ZIP codes during 1990-2010.

Heat Index	Definition description	Reference	HI days/year/ZIP (%)[a]	PTB [n (%)]	NAD [n (%)]
HI01	Mean daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	1.34 (0.9)	652 (1.1)	2678 (0.9)
HI02	Mean daily temperature > 90th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	5.41 (3.5)	2373 (3.9)	10463 (3.5)
HI03	Mean daily temperature > 98th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	0.18 (0.2)	111 (0.2)	444 (0.2)
HI04	Mean daily temperature > 99th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	0.01 (0.0)	1 (0.0)	11 (0.0)
HI05	Minimum daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	0.08 (0.1)	44 (0.1)	104 (0.0)
HI06	Maximum daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell (2011)	3.54 (2.3)	1610 (2.7)	7385 (2.5)
HI07	Maximum daily temperature ≥ 81st percentile every day, ≥ 97.5th percentile for ≥ 3 nonconsecutive days, and consecutive day average ≥ 97.5th percentile	Peng et al. (2011)	1.77 (1.2)	839 (1.4)	4106 (1.4)
HI08	Maximum daily apparent temperature[b] > 85th percentile for ≥ 1 day	Hattis et al (2012); Steadman (1984)	19.33 (12.6)	8333 (13.8)	37169 (12.3)
HI09	Maximum daily apparent temperature[b] > 90th percentile for ≥ 1 day	Hattis et al (2012); Steadman (1984)	10.91 (7.1)	4681 (7.7)	21018 (7.0)
HI10	Maximum daily apparent temperature [b] > 95th percentile for ≥ 1 day	Hattis et al (2012); Steadman (1984)	3.51 (2.3)	1568 (2.6)	6826 (2.3)
HI11	Maximum daily temperature >35°C for ≥ 1 day	Tan et al. (2007)	1.43 (0.9)	497 (0.8)	2276 (0.8)

Heat Index	Definition description	Reference	HI days/year/ZIP (%)[a]	PTB [n (%)]	NAD [n (%)]
HI12	Minimum daily temperature > 26.7°C or maximum daily temperature > 40.6°C for ≥ 2 consecutive days	(Robinson 2001)	2.90 (1.9)	1203 (2.0)	5701 (1.9)
HI13	Maximum daily heat index[c] > 80°F for ≥ 1 day	Rothfusz (1990); Steadman (1979)	125.47 (82.1)	50176 (83.0)	245833 (81.6)
HI14	Maximum daily heat index[c] > 90°F for ≥ 1 day	Rothfusz (1990); Steadman (1979)	78.26 (51.2)	31495 (52.1)	151189 (50.2)
HI15	Maximum daily heat index[c] > 105°F for ≥ 1 day	Rothfusz (1990); Steadman (1979)	3.35 (2.2)	1368 (2.3)	5581 (1.9)
HI16	Maximum daily heat index[c] > 130°F for ≥ 1 day	Rothfusz (1990); Steadman (1979)	N/A	N/A	N/A

[a]HI days/year/ZIP code percentages have the 153 days in May-September as the denominator. [b]Heat index is a function of air temperature and humidity, parameterized to take account for other environmental factors. [c]Apparent temperature is a function of air temperature, humidity, wind speed, and solar radiation.

Figure Legends

Figure 1. Percent change (95% CI) in (A) preterm birth or (B) non-accidental death on the day of a heat wave (lag0) compared with corresponding non-heat wave control days, by 15 heat wave indices (HIs). Estimates are derived from odds ratios and 95% CI estimated using unadjusted case-crossover conditional logistic regression models. See Supplemental Material, Table S2 for corresponding numeric data.

Figure 2. Number of Alabama ZIP-code level average heat wave index (HI) days per year by (A) HI02 (B) HI07 (C) HI12 and (D) HI15. Heat waves defined using HI02 have mean daily temperatures > 90th percentile for ≥ 2 consecutive days; using HI07 have maximum daily temperatures ≥ 81st percentile every day, ≥ 97.5th percentile for ≥ 3 nonconsecutive days, and consecutive day average ≥ 97.5th percentile; using HI12 have minimum daily temperatures > 26.7°C or maximum daily temperature > 40.6°C for ≥ 2 consecutive days; and using HI15 have maximum daily heat index values > 105°F for ≥ 1 day. The Gulf of Mexico borders the southwestern corner of Alabama, with the Florida panhandle separating the ocean on the southeastern corner. Western, northern, and eastern Alabama borders other states.

Figure 3. Percent change in preterm birth or non-accidental death risks by selected heat wave index (HI) lag day and heat wave durations. Estimates are derived from odds ratios and 95% CI estimated using unadjusted case-crossover conditional logistic regression models. Top panels display preterm birth risk percent increases by (A) lag day and (B) heat wave duration. Bottom panels show non-accidental death risk percent increases by (C) lag day and (D) heat wave duration. Heat wave length cut-points were determined using the median heat wave length for

each HI. See Supplemental Material, Table S1 for corresponding numeric data. Abbreviations: PTB = preterm birth; NAD = non-accidental death.

Figure 4. Percent increase in preterm birth or non-accidental on a heat wave day by heat wave index (HI) 01, 02, or 03 stratified by rurality. Top panels display preterm birth risk percent increases by (A) rural-urban commuting codes [RUCAs], (B) population density tertiles, and (C) green vegetation factor tertiles. Bottom panels show non-accidental death risk percent increases by (D) RUCAs, (E) population density tertiles, and (F) green vegetation factor tertiles. Estimates are derived from odds ratios and 95% CI estimated using unadjusted case-crossover conditional logistic regression models.

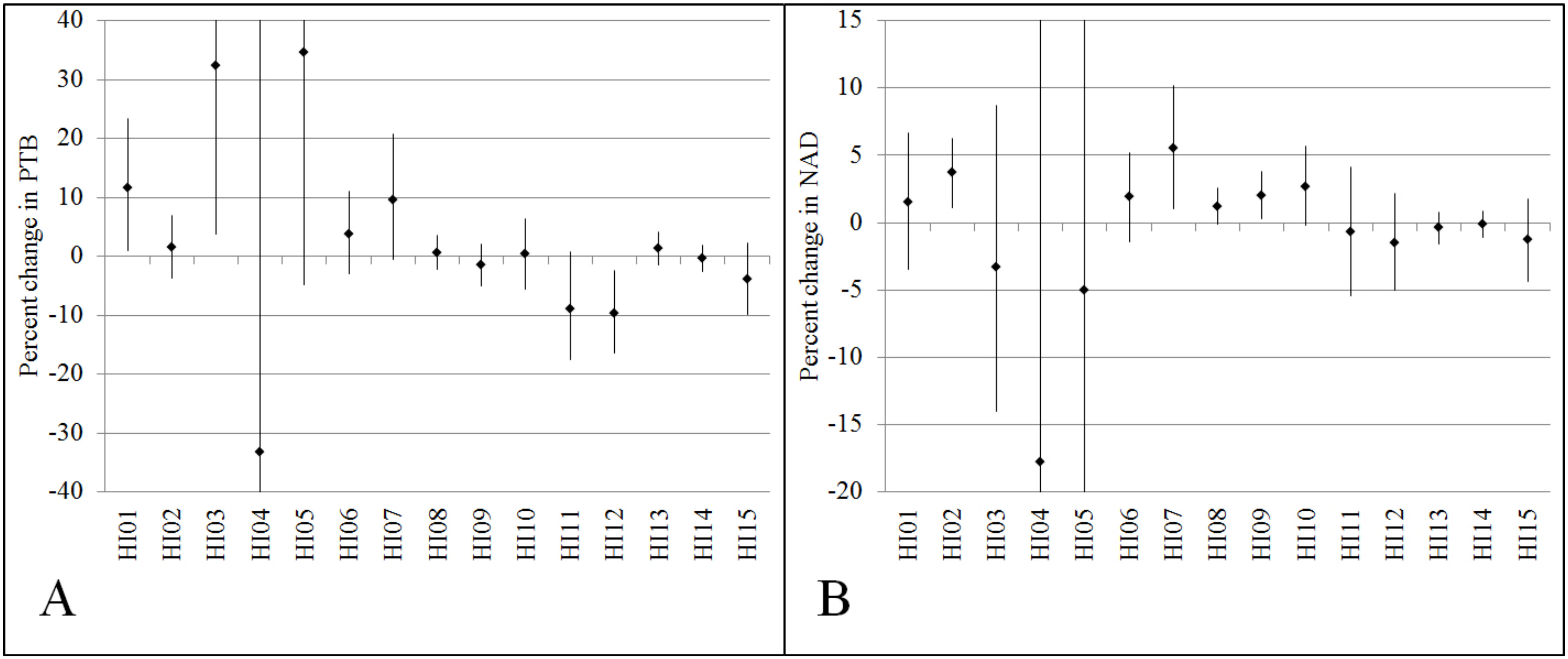
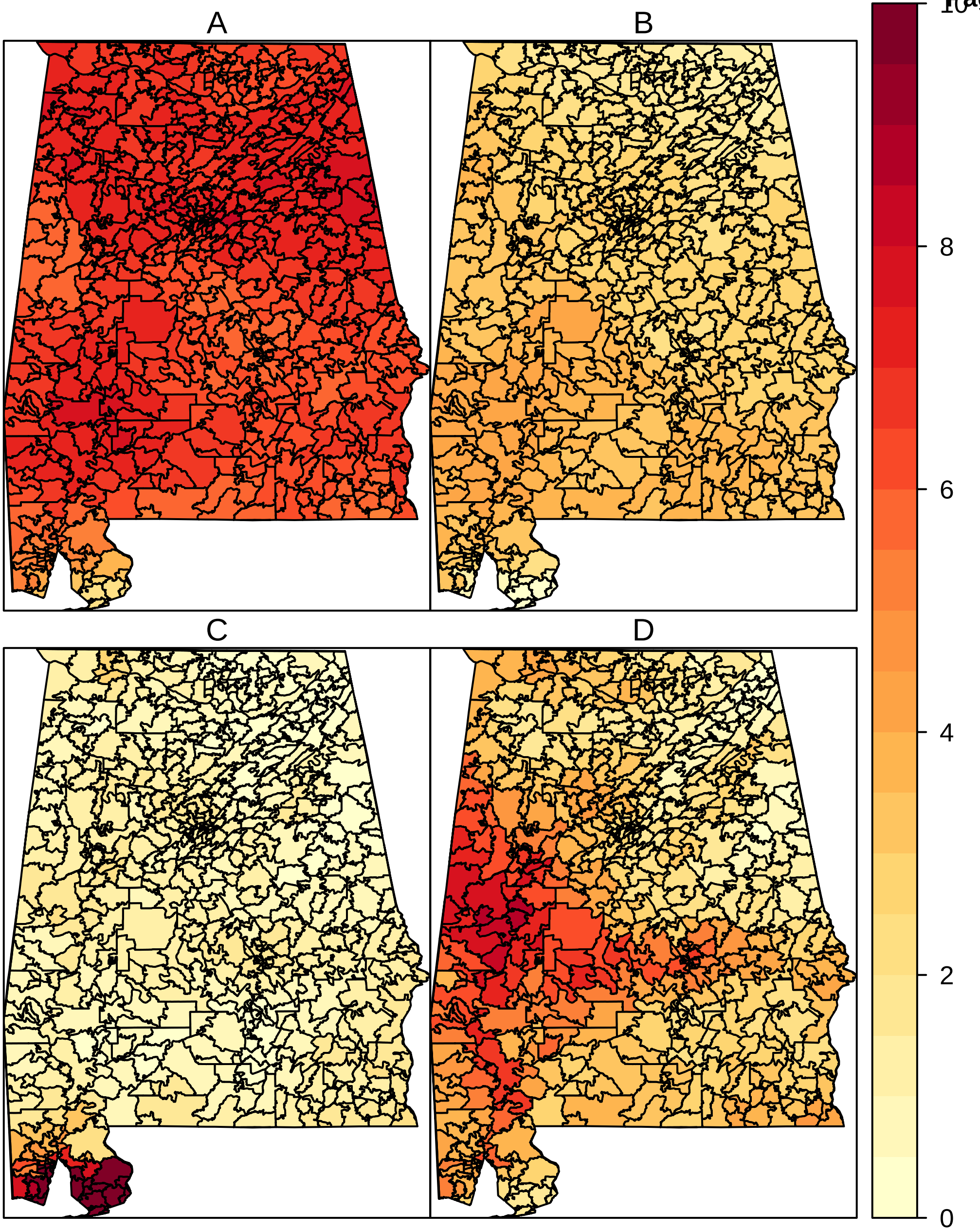

40
30
20
10
0
-10
-20
-30
-40
Percent change in PTB
HI01
HI02
HI03
HI04
HI05
HI06
HI07
HI08
HI09
HI10
HI11
HI12
HI13
HI14
HI15
A
15
10
5
0
-5
-10
-15
-20
Percent change in NAD
HI01
HI02
HI03
HI04
HI05
HI06
HI07
HI08
HI09
HI10
HI11
HI12
HI13
HI14
HI15
B

Figure 1.


A
B
C
D
10
8
6
4
2
0

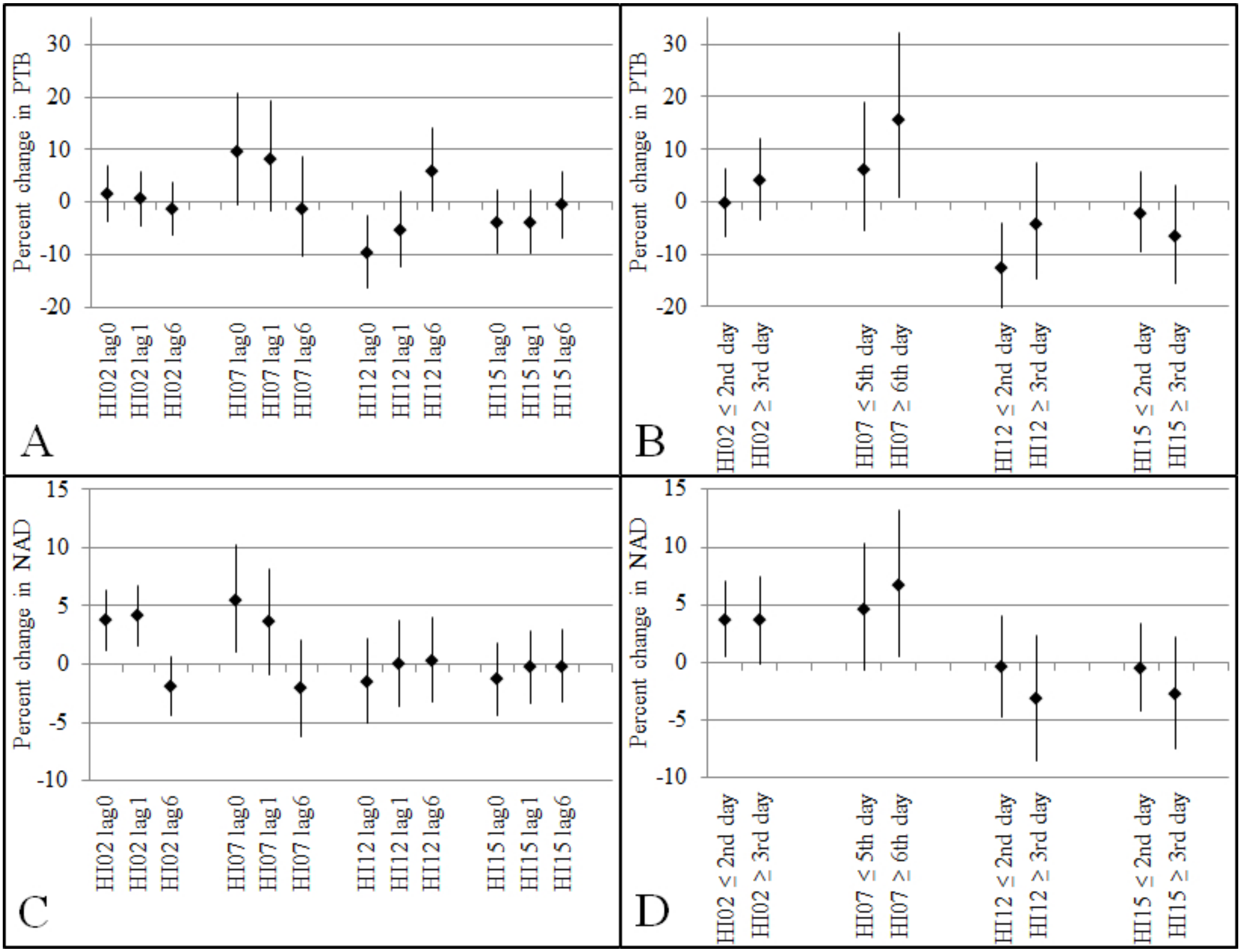

Percent change in PTB
30
20
10
0
-10
-20
HI02 lag0
HI02 lag1
HI02 lag6
HI07 lag0
HI07 lag1
HI07 lag6
HI12 lag0
HI12 lag1
HI12 lag6
HI15 lag0
HI15 lag1
HI15 lag6
A
B
HI02 ≤ 2nd day
HI02 ≥ 3rd day
HI07 ≤ 5th day
HI07 ≥ 6th day
HI12 ≤ 2nd day
HI12 ≥ 3rd day
HI15 ≤ 2nd day
HI15 ≥ 3rd day
Percent change in NAD
15
10
5
0
-5
-10
C
D

Figure 3.

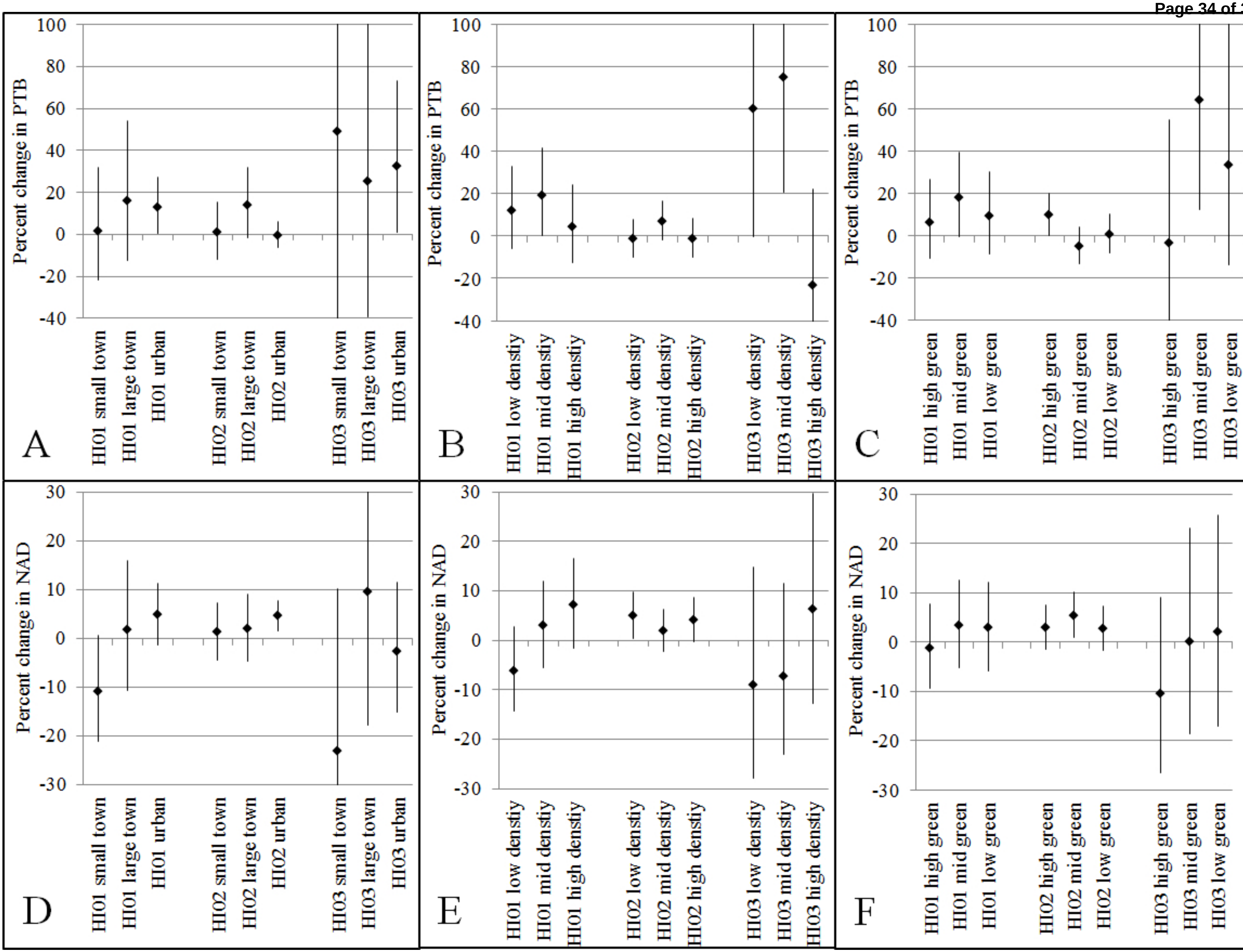

A
B
C
D
E
F
Percent change in PTB
Percent change in NAD
100
80
60
40
20
0
-20
-40
30
20
10
0
-10
-20
-30
HI01 small town
HI01 large town
HI01 urban
HI02 small town
HI02 large town
HI02 urban
HI03 small town
HI03 large town
HI03 urban
HI01 low denstiy
HI01 mid denstiy
HI01 high denstiy
HI02 low denstiy
HI02 mid denstiy
HI02 high denstiy
HI03 low denstiy
HI03 mid denstiy
HI03 high denstiy
HI01 high green
HI01 mid green
HI01 low green
HI02 high green
HI02 mid green
HI02 low green
HI03 high green
HI03 mid green
HI03 low green

Figure 4.